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Salience theory and cryptocurrency returns

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ABSTRACT

The salience theory of choice under risk shows that investor behavior drives cross-sectional cryptocurrency returns. Investors place too much weight on salient payouts, causing overvaluation of cryptocurrencies with upward salience returns and undervaluation of those with downward salience returns, leading to negative expected returns for the former and positive expected returns for the latter. The salience effect in the cryptocurrency market is more pronounced than in equity markets, making it a significant risk factor for explaining other cross-sectional returns in the cryptocurrency market. Unlike other documented return predictors, the salience theory uniquely contributes to understanding the cryptocurrency market.

1. Introduction

Cryptocurrency (crypto, hereafter) as an alternative asset class poses challenges to traditional asset-pricing theories while offering new avenues for testing theories of investor behavior. Crypto assets can be challenging to value due to their unique characteristics. Unlike fiat currencies, they lack economic fundamentals. They also differ from traditional financial assets, because they do not generate cash flows. Furthermore, unlike precious metals, crypto assets do not have a long history of trust or cultural preferences as a means of storing value. The growing number of cryptos in the market gives rise to the following question: How do investors decide which crypto to invest in or whether to invest at all?

Headlines have significantly influenced the crypto asset class, sparking investor fear of missing out on the "crypto-rush," prompting studies (Sockin and Xiong, 2023; Cong et al., 2021) to suggest the "network effect" (the increasing appeal of a platform as its user base grows) as a key driver of the crypto market's evolution. How investors process attention-grabbing fluctuations in the crypto market and the potential consequences on future crypto returns have received less attention. To this end, the salience theory, introduced by Bordalo et al. (2012), describes investors' behavior that closely matches that of the crypto market.

Salience theory is a context-dependent decision-making framework that explains choices under risk by replacing objective probabilities with distorted decision weights favoring salient payoffs that stand out compared to average alternatives (Bordalo et al., 2013a). Investors with a salience bias disproportionately prefer investments with salient upward returns and dislike those with salient downward returns. In equilibrium, the salience-based asset-pricing model proposed by Bordalo et al. (2013a) predicts that investments with conspicuous upside potential (downside risk) should generate lower (higher) returns.

Cosemans and Frehen (2021) and Cakici and Zaremba (2022) provide evidence supporting the impact of the salience theory on cross-sectional pricing in the United States and international equity markets. Notably, the salience effect was more pronounced for stocks with higher limits to arbitrage and during periods of elevated investor sentiment, reinforcing the mispricing explanation (Cosemans and Frehen, 2021). In line with these findings, Cakici and Zaremba (2022) demonstrate that the salience effect is evident when arbitrage opportunities are limited, such as in micro firms, high idiosyncratic risk countries, and during extreme market conditions characterized by significant economic uncertainty and volatility. The crypto market is an emerging asset class with high uncertainty and limited fundamental information available to investors. Hirshleifer (2001) argues that uncertainty allows investors to follow their subjective estimations and ignore objective valuations.

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The emerging and non-mainstream nature of the crypto market creates an environment that is more likely to attract investors with a salience bias. For example, Cakici and Zaremba (2022) note that sentiment and the resulting salience theory effect are more likely to influence retail equity investors. Therefore, substantial evidence exists to conjecture that salience theory could be a critical mechanism in determining the pricing of cryptos; its effect would be stronger in the crypto market than in other decision-making contexts, including equity markets.

This study examines whether the salience effect exists on cross-sectional crypto returns. We use data from over 4,000 coins with a market value greater than one million USD from "Coinmarketcap.com" from January 2014 to June 2021. Following Cosemans and Frehen (2021), we construct a salience measure, ST, that effectively measures the difference between salience- and equal-weighted returns during the formation period (weekly or monthly). ST quantifies the extent of salience thinking in distorting investors' expectations of future returns compared to objectively realized past returns. The salience-based asset-pricing model primarily predicts that cryptos with salient upsides (positive ST) have lower future returns than those with salient downsides (negative ST).

Our empirical study comprises two parts. First, we study the predictability of ST on cross-sectional crypto returns. Second, we investigate the viability of ST as a cross-sectional pricing factor, assessing its ability to account for other cross-sectional predictabilities in the crypto market.

The predictability study employed single-portfolio sorting to illustrate the economic and statistical significance of the ST effect. Our findings indicate that cryptocurrencies with salient upsides yield lower returns over the following month than those with salient downsides. The univariate portfolio analysis revealed that the average return for the zero-cost strategy, which involves purchasing high-ST cryptocurrencies, varies from −25.9% (t-value = −8.7) monthly for the equal-weighted (EW) portfolio to −32.4% (t-value = −2.3) for the value-weighted (VW) portfolio. These figures are over 20 times greater than those reported in the US equity market (Cosemans and Frehen, 2021) and are considerably larger than the micro-stock results, the most substantial findings documented in the international equity markets of Cakici and Zaremba (2022).[1] Moreover, the salience effect is on par with the strongest factors documented thus far in crypto market research (Liu et al., 2022).

Subsequently, we demonstrated the robustness of ST's predictability, showing that it yields significant alpha when controlled for the Liu-Tsyvinski-Wu (LTW) three-factor model (Liu et al., 2022). Furthermore, ST has incremental predictability for future crypto returns in the Fama-MacBeth regression analyses when accounting for cross-sectional determinants in the ST and crypto literature (Cosemans and Frehen, 2021; Liu et al., 2022).

In the pricing factor study, if the ST serves as one of the primary pricing effects in the crypto market, we anticipate its ability to explain other cross-sectional pricing patterns. For example, Bordalo et al. (2013a) demonstrate that the ST is valuable in deciphering equity asset pricing anomalies such as the preference bias for highly skewed assets, the growth-value puzzle, and the aggregate equity premium puzzle. We created an ST factor using the factor construction method proposed by Liu et al. (2022) to investigate this potential in the crypto market. Our findings suggest that the ST factor could potentially supplement the momentum factor in the LTW three-factor model, accounting for other cross-sectional return strategies documented in Liu et al. (2022) and additional behavioral anomalies, including prospect theory (Barberis et al., 2016), skewness (Harvey and Siddique, 2000), and downside beta (Ang et al., 2006).

We conducted additional robustness tests to deepen our understanding of the crypto market's ST return predictability and pricing factor roles. Regarding ST's predictability, we demonstrate that 1) the ST effect is also observable in a time-series context, where the salience of crypto market returns, compared to other investment opportunities, negatively predicts the asset class's future returns. Furthermore, 2) the cross-sectional ST effect is positively correlated with uncertainty and attention in the crypto market but negatively correlated with uncertainty in the stock market and the economy. These findings confirm that investors influenced by salience bias will likely be risk-seekers drawn to crypto markets when other asset markets are relatively calm. Their activities intensify with greater investor attention to the crypto market, corroborating that behavioral bias underlies this effect.

Regarding the pricing factor study, we offer more detailed comparisons between ST and existing factors, including the prospect theory from Kahneman and Tversky (1979) (KT), idiosyncratic volatility, market beta, momentum, and reversal using double sorting, correlations, and a pairwise comparison of return predictability in Fama-Macbeth regressions. ST generally prevails over the other effects, confirming that the salience measure is theoretically and empirically distinct. The ST measure captures the cross-sectional and time-series information on crypto returns. Each return for a given period is initially compared cross-sectionally with other crypto returns to obtain a salience measure. We then apply this measure in a time-series context for each crypto to determine how much the salience factor influences its expected return, thereby capturing information that differs from the existing cross-sectional characteristics.

This study offers new insights into the valuation of crypto assets and the relevance of the ST in asset pricing. First, we demonstrate that the behavior of crypto investors can be explained by the ST in decision-making, thereby expanding the theoretical and empirical efforts to understand the drivers of this market. According to Sockin and Xiong (2023), network effects suggest that news and investor sentiment explain token price fluctuations and expected returns. Similarly, Cong et al. (2021) provide a dynamic model illustrating the impact of endogenous user adoption on a platform's success and token price. Speculative motives and sentiments can influence potential users' decisions to participate on a platform, explicitly connecting investor attention to and expectations of the platform's growth. Salience theory goes one step further by describing how investors may form expectations based on salient payoffs that capture their attention. Our empirical evidence confirms a strong ST effect in crypto returns' cross-section and time series. This approach demonstrates that ST is a contender as one of the risk factors for cross-sectional returns, which is particularly appealing, as it stems from a behavioral theory model, providing a solid foundation for interpreting the factor.

Second, we present additional evidence on the conditions under which the ST may be more relevant in explaining asset prices. The crypto market aligns well with the conditions Cakici and Zaremba (2022) and others identified for observing the ST effect: micro caps, extreme uncertainty, and potentially less sophisticated investors. We show that a strong ST effect dominates prospect theory and the preference for skewness explanations. Furthermore, we demonstrate that the ST effect differs from short-term reversal, which is challenging to disentangle in an equity market. Our findings confirm that the salience effect is much stronger for assets more difficult to value, mainly when fundamental information is reduced.

Finally, we reveal that the salience effects are significantly stronger in the crypto market than in the traditional financial market, even by microcap standards. This finding implies a disproportionately large group of salience-driven investors in the crypto market, underscoring the importance of regulations and investor protection.

The remainder of this study is organized as follows. Section 2 describes the data source and construction of a salience effect measure. Section 3 analyzes the effect of ST on cross-sectional return predictability, and Section 4 reports the analyses that considered ST as a risk

[1] Cryptocurrency market returns were generally quite large during our investigation period, as documented by Liu and Tsyvinski (2021), who show an average monthly return of 20.44% and a standard deviation of 70.80%.

factor. Section 5 outlines the series of robustness checks, and we conclude with our findings in Section 6.

2. Data and methodology

2.1. Data sources

Following similar studies, we retrieved crypto prices from Coinmarketcap.com (Liu and Tsyvinski, 2021; Liu et al., 2022). Our sample's daily crypto price observations ranged from January 1, 2014, to June 30, 2021. The collected dataset contained crypto symbols as identifiers, daily prices, trading volume in USD, and market capitalization of the included cryptos. The samples did not contain any stablecoins. Cryptos are traded on centralized or decentralized electric exchanges, 24 hours a day, 7 days a week. In general, the crypto market has no exchange close time. We include all calendar days with crypto transactions and calculate the returns using the whole day closing price from 0:00:00.000 to 23:59:59.999 UTC.

2.2. ST measure

Following Bordalo et al. (2016) and Cosemans and Frehen (2021), we constructed an ST measure using the following steps. First, we calculated the salience of each crypto's daily payoff within the measurement period. When choosing among cryptos, we assumed that investors infer a set of future return states from the distribution of past returns. Our primary analysis assumed that the daily returns over the past week or month form this state space. We measured the salience of the return ($r_{i,s}$) of crypto i on day s by its distance from the average return across all cryptos in the market on that day ($\bar{r}_s$):

$$\sigma(r_{i,s},\bar{r}_s)=\frac{|r_{i,s}-\bar{r}_s|}{|r_{i,s}|+|\bar{r}_s|+\theta}, \tag{1}$$

where $\bar{r}_s=\sum_{i=1}^{N} r_{i,s}/N$ with N denoting the number of cryptos available on the market. θ is included to control for the salience of 0 payoffs. Following Cosemans and Frehen (2021), we set $\theta=0.1$.

Second, we calculated the salience weights. Given the salience function in Equation (1), the salient thinker ranks each payoff and replaces the objective state probabilities with the salience weights. For the objective state probabilities, S denotes the set of states, which is the number of trading days within the ranking period, where each state s occurs with an equal probability π_s so that $\pi_s=1/S$. The salience-weighted probability is then given by:

$$\tilde{\pi}_{i,s}=\pi_s\times\omega_{i,s}, \tag{2}$$

Here, $\tilde{\pi}_{i,s}$ denotes the salience-weighted subjective state probability and $\omega_{i,s}$ is the salience weight defined as

$$\omega_{i,s}=\frac{\delta^{k_{i,s}}}{\sum_{s'}\delta^{k_{i,s'}}\cdot\pi_{s'}}, \tag{3}$$

here δ captures the degree to which salience distorts the decision. When $\delta=1$, no distortion occurs; when $\delta\to 0$, there is a maximum salience distortion in that the investor only considers the most salient payoff. Following Bordalo et al. (2012) and Cosemans and Frehen (2021), we set $\delta=0.7$ in our analyses. Furthermore, $k_{i,s}$ is the rank of the salience payoff $r_{i,s}$ among the daily return of a given crypto in the measurement period and ranges from 1 (most salient) to S (least salient); $\pi_{s'}=1/S$ denotes the objective probability for each state.

Third, the salience effect — the extent to which salience thinking influences the expected return — is then measured by the covariance of the decision weights ($\omega_{i,s}$) and the crypto return ($r_{i,s}$) over the estimation period according to the salience-based asset-pricing framework (Bordalo et al., 2013a).

Table 1
Summary statistics on portfolio analysis.

Year	Counts	Market Cap (million USD)		Volume (thousand USD)	
		Mean	Median	Mean	Median
2014	100	309.38	5.97	1,655	47
2015	83	179.88	4.70	1,583	15
2016	171	210.32	4.44	2,488	25
2017	796	632.23	13.91	31,778	201
2018	1,592	497.38	12.51	30,156	212
2019	1,957	293.18	5.90	75,832	172
2020	2,614	763.91	6.71	134,423	281
2021	3,701	1,108.23	13.72	232,859	516

Table 1 presents the number of cryptos, the mean and median market capitalization, and the mean and median trading volume in USD per year. The sample comprises actively traded cryptos with a market capitalization of over 1 million USD within the sample period from January 2014 to June 2021.

$$ST_i=Cov[\omega_{i,s},r_{i,s}]=\sum_{s}^{S}\pi_s\omega_{i,s}r_{i,s}-\sum_{s}^{S}\pi_s r_{i,s} \tag{4}$$
$$=\mathbb{E}^{ST}[r_{i,s}]-\bar{r}_s,\qquad \forall i\in N,$$

where $\mathbb{E}^{ST}[.]$ denotes the salience-biased expected value. ST_i effectively measures differences between salience-weighted and EW returns in the measurement period (second equality). It quantifies the extent of salience thinking on distorting investors' expectations about future returns compared to objectively realized past returns. When $ST<0$, it suggests that the lowest payoffs of an asset are the salient ones; the investors focus on downside risks, leading to a positive "risk" premium (positive expected return in the next period). When $ST>0$, it suggests that the highest payoffs of an asset are the salient ones; the investors focus on upside potential, resulting in a negative "risk" premium (negative expected return in the next period).

The derivation of the salience effect measure is grounded in the salience-based asset-pricing theory of Bordalo et al. (2013a) and closely adheres to the empirical design of Cosemans and Frehen (2021). This salience measure is theoretically and empirically distinct, capturing both cross-sectional and time-series information on a crypto's return. First, each return for a given period is compared cross-sectionally with other returns to obtain a salience measure. Second, each security employs this salience measure in a time-series context to determine how much the salience factor influences its expected return.

Our portfolio sorting analysis computed the ST parameter specified in Equation (4) using the daily salience measure for each crypto week or month. We construct a quintile portfolio by sorting the ST measures and calculating the excess portfolio returns for the next period.

2.3. Summary statistics

Table 1 presents the number of cryptos. The number of coins and tokens in the sample that satisfied all filters increased from 100 in 2014 to 3,701 in 2021; the sample's mean (median) market capitalization also increased significantly during this period. A significant difference between the mean and median suggests a substantial outlier (notably Bitcoin). Volume increases much faster than market capitalization, which is consistent with the emerging nature and growth of this class of assets.

Previous asset-pricing studies, ST, and crypto markets inform additional control variables, mainly constructed from the trading prices and volumes of cryptos. Online Appendix 2 discusses these variables, while Appendix Table A.1 summarizes all variable constructions.[2]

[2] Summary statistics and correlations of the key variables can be found in Online Appendix Table OA1.

Table 2
Salience Theory effect — portfolio sorting.

	Weekly Returns		Monthly Returns	
	Equal-Weighted	Value-Weighted	Equal-Weighted	Value-Weighted
1 (Low)	0.020***	0.054***	0.175***	0.381***
	[4.065]	[5.850]	[7.149]	[2.682]
2	0.000	0.013***	0.045**	0.102***
	[0.162]	[2.777]	[2.029]	[3.595]
3	0.000	0.014***	-0.010	0.084***
	[0.130]	[3.275]	[-0.601]	[3.508]
4	-0.005**	0.016***	-0.033*	0.092**
	[-2.287]	[3.312]	[-1.842]	[2.514]
5 (High)	-0.014***	0.024**	-0.084***	0.057**
	[-4.653]	[2.518]	[-4.197]	[2.227]
High - Low	-0.034***	-0.030**	-0.259***	-0.324**
t-Stat	[-5.223]	[-2.226]	[-8.701]	[-2.269]

Table 2 presents the average returns of the single-sorted portfolios using the salience theory (ST) measure. The sample consists of actively traded cryptos with a market capitalization of over 1 million USD within the sample period from January 2014 to June 2021. Each week (month), the cryptos are sorted into quintile portfolios according to the salience effect measure of the previous week (month). Each portfolio was held for one week (months). The "Equal-Weighted" and "Value-Weighted" columns report the one week (one month) ahead excess returns of each portfolio with equal-weighted and value-weighted, respectively. Using the corresponding sorting variable, the "High - Low" row reports the average return difference between the highest and lowest sorting value portfolios. The "*t*-Stat" row reports the Newey-West robust *t*-statistic.

3. ST and the predictability of cross-sectional crypto returns

3.1. Univariate portfolio sorts

Table 2 presents the average returns of the single-sorted portfolios using the ST measure. The sample comprises actively traded cryptos with a market capitalization of over 1 million USD during the sample period from January 2014 to June 2021. Each week (month), cryptos are sorted into quintiles according to the salience effect measure of the prior week (month). Each portfolio was held for one week (month). Two considerations affected the decision regarding different return windows. First, given the shorter history and potentially faster-moving market for crypto assets, the existing literature often uses weekly frequencies. Weekly frequency was the primary choice for comparison with existing studies. Second, asset-pricing studies on equity markets have traditionally been based on monthly data, therefore, we present the monthly findings for our main baseline to compare the magnitudes with those in the equity market. We only reported the weekly frequency, for the other findings in this study. The monthly findings produced a consistent conclusion, which can be found in the Online Appendix.

Table 2 shows that cryptos with salient upsides earn lower returns over the next period than cryptos with salient downsides. This result is consistent with the findings in the equity market by Cosemans and Frehen (2021) and Cakici and Zaremba (2022). Three additional observations arise from these crypto market analyses. First, the magnitude of the salience effect is economically much bigger than those in the equity markets. For example, the average return for the long-short strategy that buys high and sells low ST cryptos generates −25.9% (t-value = −8.7) monthly for the EW portfolio and −32.4%(t-value = −2.3) for the VW portfolio. These are more than 20 times the magnitude of those documented in the U.S. equity market with −1.28% and −0.6% monthly excess returns for EW and VW, respectively (Cosemans and Frehen, 2021). The ST effect in the crypto market is also markedly larger than in the micro stock results, representing the strongest findings in the equity market, as documented by Cakici and Zaremba (2022). They found that the ST strategy generated -1.0% and −0.52% monthly excess returns for EW and VW, respectively.

Second, the salience effect is comparable to the strongest factors documented in the crypto market research. For example, Liu et al. (2022) found a VW size factor premium of 3.4% to 4.1% per week. Our weekly findings for a 3.0% VW weekly return are comparable to this magnitude. Furthermore, the monthly salience effect is much stronger in the crypto market. The monthly VW return for the ST effect in the crypto market is annualized (multiplied by 12) to 388.8%, whereas the largest weekly size effect is annualized (multiplied by 52) to 213.2%; however, it is important to be cautious about such large return strategies. The salience effects require supply (salience price movement) and demand (the attention of salience investors with funds to participate); both can be time varying. In a subperiod analysis, we confirm that the ST effect is time-varying (in the Online Appendix). The key implication is that there is a risk of engaging in such a strategy every year.

Third, the EW results were much stronger than the VW results, consistent with the potential size effect suggested by Cakici and Zaremba (2022). The EV results place more weight on small cryptos, demonstrating a stronger effect, however, a later analysis shows that the ST effect in the crypto market is not restricted to small-cap cryptos. In the robustness test section, we further study the relationship between the market cap and the ST effect (Section 5.3.3). Overall, Table 2 demonstrates a strong ST effect that is statistically significant and economically large.

3.2. Controlling for existing crypto risk factors

We considered the relationship between the ST effect and known risk factors. Table 3 presents the alphas and details of the regression explaining crypto excess returns in quintile portfolios using the LTW three-factor model (Liu et al., 2022). We construct the crypto market index using the EW returns of all available coins and tokens. The size and momentum factors in the weekly return analysis follow the construction approach proposed by Liu et al. (2022). The size factor was constructed like the weekly returns for the monthly factors. We constructed the monthly momentum factor using one-month lagged returns.

Table 3 shows that ST generates a 3.2% alpha weekly (annualized 166.4%) and 24.6% alpha monthly (annualized 295.2%), as shown in the "High-Low" columns.[3] Regarding the factor loading, the weekly regressions show that the ST portfolio loads a positive size factor but

[3] To alleviate the concern about the impact of outliers, we tried winsorizing the raw return on [0.5%, 99.5%] and [1%, 99%], and the results remain with similar magnitude. Extreme cases do not drive portfolio alphas.

Table 3
Risk factor analyses of salience effect using LTW three-factor model.

	Panel A: Weekly Returns					
	1 (Low)	2	3	4	5 (High)	High - Low
α	0.020***	0.001	0.000	-0.005**	-0.011***	-0.032***
t(α)	[3.635]	[0.270]	[-0.082]	[-2.198]	[-3.448]	[-4.326]
β(CMKT)	0.096**	0.006	-0.051**	-0.006	0.011	-0.085
t(β(CMKT))	[1.998]	[0.250]	[-2.337]	[-0.264]	[0.376]	[-1.352]
β(SIZE)	-0.023	0.009	0.003	0.000	0.029***	0.052**
t(β(SIZE))	[-1.447]	[1.119]	[0.471]	[-0.031]	[3.037]	[2.474]
β(MOM)	0.021	0.009	-0.004	-0.001	-0.038***	-0.059**
t(β(MOM))	[1.087]	[0.866]	[-0.401]	[-0.122]	[-3.263]	[-2.302]
Adj. R^2	0.0195	0.0078	0.0165	0.0002	0.0418	0.0307

	Panel B: Monthly Returns					
	1 (Low)	2	3	4	5 (High)	High - Low
α	0.178***	0.051*	0.006	-0.028	-0.068***	-0.246***
t(α)	[5.882]	[1.932]	[0.321]	[-1.242]	[-2.698]	[-6.381]
β(CMKT)	-0.248***	-0.273***	-0.177***	-0.154**	-0.136**	0.112
t(β(CMKT))	[-3.224]	[-4.042]	[-3.563]	[-2.679]	[-2.112]	[1.138]
β(SIZE)	0.013	0.027	0.043*	0.026	0.045	0.032
t(β(SIZE))	[0.383]	[0.899]	[1.955]	[1.017]	[1.577]	[0.736]
β(MOM)	0.024	0.029	0.040	0.016	0.035	0.011
t(β(MOM))	[0.666]	[0.912]	[1.674]	[0.592]	[1.145]	[0.230]
Adj. R^2	0.1148	0.1701	0.1669	0.0950	0.0813	0.0292

Table 3 presents the details of the regressions explaining the crypto-excess returns in the ST quintile portfolios using the LTW three-factor model proposed by Liu et al. (2022). The model specifications are as follows.

$$R_i - R_f = \alpha^i + \beta_1^i CMKT + \beta_2^i SIZE + \beta_3^i MOM + \epsilon_i.$$

CMKT is the VW cryptocurrency return. SIZE is the size factor constructed from the market capitalization of the coins. MOM is the cumulative past crypto returns. More detailed variable definitions are provided in Table A.1. The sample consists of actively traded cryptos with a market capitalization of over 1 million USD within the sample period from January 2014 to June 2021. ***, **, and * denote significant levels at 1%, 5%, and 10%, respectively.

a negative momentum factor. No significant factor loading is shown in the monthly regression, suggesting that the ST effects were independent of the existing factors. The finding confirms that known risk factors cannot explain the salience effect.[4]

3.3. Fama-MacBeth cross-sectional regressions

We examined the cross-sectional predictability of crypto returns with and without ST measures, including a list of control variables. Table 4 reports the estimated regression coefficients and t-statistics (in parentheses) from the Fama-MacBeth cross-sectional regressions for weekly (panel A) and monthly returns (panel B). Following Cosemans and Frehen (2021), we included a list of cross-sectional determinants. The control variable is described in the Online Appendix 2 and Table A.1.

Panel A in Table 4 shows that ST has significant predictability for future crypto returns in all specifications. It can explain 10% of the future cross-sectional weekly returns, as indicated by the average R^2. Furthermore, the ST effect is robust when controlling for other firm-level risks, such as liquidity, lottery demand, prospective theory value, skewness preference, and downside risk measures. While the t-value indicates the statistical significance is reduced, the magnitude seems higher, especially when other behavioral controls, such as TK and SKEW, are added. A clear incremental improvement occurred in explanatory power when ST was included. The average adjusted R-squared increases from 32% (Column 11) to 45% (Column 10) when the ST variable was added to the regression with all control variables, representing a 39% increase in explanatory power. The monthly results in Panel B are consistent with the weekly findings, with the ST variable having increased t-values.

4. ST as a potential risk factor in the crypto market

If the ST effect captures one of the key trading behaviors of crypto investors, it may explain other return "anomalies" in this emerging asset class. We further explored the relationship between ST and other crypto market return anomalies, constructing the ST factor similar to that of Liu et al. (2022). Each week, we partitioned the cryptos into three salience groups using the ST measure: the bottom 30% (down-salience), the middle 40% (non-salience), and the top 30% (up-salience). Furthermore, we then formed VW portfolios for each group. The crypto-ST factor is the return difference between the up-salience and down-salience portfolios; therefore, the ST premium is negative for this construction. We strictly followed Liu et al. (2022) to construct the other three crypto factors: the market, size, and momentum.[5]

Table 5 presents the alphas from the factor model regressions explaining the crypto-excess returns in the hedge portfolios (high-low) sorted by crypto characteristic variables studied in the extant literature, including six different factor model specifications. Specifically, Models

[4] We also test the alpha including equity factors — Fama and French (1993) three-factor and Carhart (1997) momentum factor — and including both equity and LTW three factors in a full seven-factor (Full7) model; however, these specifications do not explain the ST effect (Table OA2).

[5] For completeness, we also constructed equal-weighted factor returns. We reported on VW analyses to be consistent with Liu et al. (2022). Analyses of EW portfolios using EW factors can be found in the Online Appendix Table OA3.

Table 4
Fama-MacBeth cross-sectional regressions.

	Panel A: Weekly Returns										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ST	-0.355***	-0.354***	-0.374***	-0.434***	-0.452***	-0.320**	-0.309*	-0.433**	-0.450**	-0.554**	
	[-3.751]	[-3.861]	[-4.093]	[-4.504]	[-4.458]	[-1.993]	[-1.922]	[-2.514]	[-2.555]	[-2.564]	
BETA		-0.002	-0.002	0.000	0.000	-0.002	-0.001	0.001	0.000	0.000	-0.001
		[-0.882]	[-0.943]	[0.068]	[-0.109]	[-0.275]	[-0.100]	[0.143]	[0.053]	[0.064]	[-0.123]
SIZE		-0.002***	-0.002***	-0.004***	-0.003***	-0.003***	-0.003***	-0.002**	-0.002*	-0.001	-0.001
		[-2.909]	[-2.813]	[-4.026]	[-3.541]	[-3.472]	[-3.130]	[-2.234]	[-1.707]	[-1.026]	[-0.832]
MOM			0.005	0.007	0.005	0.011	0.009	0.007	0.008	0.007	0.007
			[0.635]	[0.998]	[0.721]	[1.401]	[1.112]	[0.754]	[0.818]	[0.750]	[0.751]
AGE				0.001	0.000	0.000	-0.001	-0.003	-0.006	-0.007	-0.007
				[0.236]	[-0.024]	[0.120]	[-0.141]	[-0.857]	[-1.214]	[-1.353]	[-1.566]
IVOL				-0.035***	-0.037***	-0.007	-0.008	0.006	0.007	-0.011	-0.016
				[-3.531]	[-3.068]	[-0.213]	[-0.221]	[0.151]	[0.183]	[-0.277]	[-0.427]
ILLIQ					116.409	174.284	218.263*	265.542	200.127	219.45	164.181
					[1.049]	[1.390]	[1.752]	[1.491]	[1.097]	[1.384]	[1.466]
MAX						0.011	0.000	-0.072	-0.081	-0.066	0.040
						[0.146]	[0.002]	[-0.793]	[-0.857]	[-0.687]	[0.471]
MIN						0.100	0.084	0.018	0.039	0.004	0.073
						[1.173]	[0.951]	[0.196]	[0.405]	[0.040]	[0.822]
TK							0.085	0.146	0.135	0.119	0.151
							[0.996]	[1.301]	[1.157]	[0.981]	[1.247]
SKEW								0.000	-0.000	-0.002	-0.003
								[0.176]	[-0.006]	[-0.450]	[-0.774]
COSKEW								1.821	1.870	2.050	5.022
								[0.339]	[0.341]	[0.376]	[0.986]
ISKEW									0.000	0.001	0.001
									[-0.061]	[0.182]	[0.216]
DBETA										-0.006	-0.002
										[-1.225]	[-0.475]
Intercept	-0.001	0.036***	0.041***	0.072***	0.065***	0.058***	0.057***	0.047**	0.046**	0.042*	0.035
	[-0.148]	[2.719]	[2.864]	[4.587]	[4.141]	[3.821]	[3.342]	[2.446]	[2.192]	[1.866]	[1.564]
Avg. R^2	0.1096	0.1665	0.2059	0.2664	0.2922	0.3614	0.3832	0.4181	0.4274	0.4475	0.3222

	Panel B: Monthly Returns										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ST	-2.630***	-2.685***	-2.652***	-2.529***	-2.608***	-2.054***	-1.979***	-1.803***	-1.849***	-1.803***	
	[-4.533]	[-4.617]	[-4.773]	[-4.502]	[-4.619]	[-4.324]	[-4.523]	[-4.352]	[-4.089]	[-4.104]	
BETA		0.001	-0.005	-0.022*	-0.020*	-0.046*	-0.058***	-0.051**	-0.050**	-0.040**	-0.046**
		[0.130]	[-0.420]	[-1.734]	[-1.799]	[-1.870]	[-2.720]	[-2.497]	[-2.387]	[-2.079]	[-2.476]
SIZE		0.021***	0.022***	0.027***	0.027***	0.025***	0.025***	0.025***	0.022***	0.023***	0.023***
		[6.552]	[7.812]	[7.813]	[7.931]	[8.269]	[7.927]	[5.383]	[3.825]	[3.304]	[3.384]
MOM			0.042***	0.042***	0.043***	0.036**	0.049***	0.049***	0.052***	0.055***	0.053***
			[3.061]	[2.947]	[3.034]	[2.328]	[3.023]	[3.202]	[3.395]	[3.626]	[3.716]
AGE				-0.001	-0.002	0.019	-0.003	-0.027	-0.030	-0.015	0.000
				[-0.093]	[-0.196]	[0.838]	[-0.257]	[-1.627]	[-1.534]	[-0.890]	[0.024]
IVOL				0.134***	0.143***	0.082	0.025	-0.024	-0.02	0.018	0.045
				[3.206]	[3.060]	[0.703]	[0.242]	[-0.225]	[-0.173]	[0.153]	[0.373]
ILLIQ					75.142	-76.72	6.585	359.266	449.632	548.692	422.713
					[0.378]	[-0.742]	[0.051]	[1.207]	[1.322]	[1.360]	[1.259]
MAX						0.459***	0.576***	0.632***	0.599***	0.654***	0.747***
						[3.117]	[4.420]	[5.065]	[4.603]	[4.365]	[4.957]
MIN						0.155	0.122	0.134	0.141	0.255	0.364**
						[0.855]	[0.737]	[0.869]	[0.844]	[1.325]	[2.201]
TK							0.143	0.310	0.324	0.229	0.302
							[0.611]	[0.986]	[0.979]	[0.517]	[0.687]
SKEW								-0.002	-0.004	-0.003	-0.005
								[-0.463]	[-0.283]	[-0.194]	[-0.326]
COSKEW								-0.141	-0.186	-0.497	-0.579
								[-0.227]	[-0.288]	[-0.793]	[-0.886]
ISKEW									0.008	0.005	0.005
									[0.477]	[0.320]	[0.335]
DBETA										-0.001	-0.000
										[-0.038]	[-0.014]
Intercept	0.007	-0.327***	-0.342***	-0.453***	-0.449***	-0.460***	-0.457***	-0.438***	-0.405***	-0.444***	-0.443***
	[0.502]	[-5.611]	[-6.503]	[-6.892]	[-6.963]	[-7.573]	[-7.172]	[-4.526]	[-3.678]	[-2.799]	[-2.905]
Avg. R^2	0.0614	0.1265	0.1627	0.2181	0.2338	0.3113	0.3331	0.3623	0.3732	0.3940	0.3755

Table 4 reports the estimated regression coefficients of the *t*-statistics (in brackets) from Fama-MacBeth cross-sectional regressions for crypto returns. The sample consists of actively traded cryptos with a market capitalization of over 1 million USD within the sample period from January 2014 to June 2021, including 391 weeks (90 months). The Fama-MacBeth regression uses weekly returns (Panel A) and monthly returns (Panel B). ST is the salience theory measure. BETA denotes the beta for the market return. SIZE is the market capitalization of cryptos. MOM denotes the lagged one-day return. VOLM is the logarithm of the trading volume. IVOL denotes the idiosyncratic volatility estimated from the market model. ILLIQ denotes the illiquidity level using the daily Amihud measure. MAX and MIN are the maximum and minimum daily returns within the estimation period. TK is the prospective theory value. SKEW is the daily return skewness. COSKEW is the co-skewness of the daily returns with the market returns. ISKEW is the idiosyncratic skewness of the residuals from the market model. DBETA is the downside beta estimated from the regression of the daily excess crypto return on the daily market return. The variable definition is specified in Table A.1. The *t*-statistics reported in brackets are based on the Newey and West (1987) standard error.

Table 5
Alpha of asset pricing models on different anomalies.

Panel A		M1	M2	M3	M4	M5	M6
ST	α	-0.030**	-0.033**	-0.033**	-0.017	-0.017	-0.018
	t(α)	[-2.247]	[-2.353]	[-2.367]	[-0.519]	[-0.515]	[-0.538]
MCAP	α	-0.127***	-0.010	-0.009	-0.128***	-0.010	-0.009
	t(α)	[-5.297]	[-1.563]	[-1.362]	[-5.334]	[-1.578]	[-1.351]
PRC	α	-0.033**	0.003	-0.015	-0.039***	-0.004	-0.014
	t(α)	[-2.438]	[0.215]	[-1.316]	[-3.139]	[-0.410]	[-1.297]
MAXDPRC	α	-0.038***	-0.012	-0.029	-0.044***	-0.019*	-0.029
	t(α)	[-2.970]	[-1.004]	[-0.652]	[-3.671]	[-1.658]	[-0.655]
MOM 1-week	α	0.042***	0.036***	0.026	0.038***	0.032***	0.027
	t(α)	[4.107]	[3.457]	[0.637]	[3.901]	[3.169]	[0.666]
MOM 2-week	α	0.043***	0.040***	0.026	0.040***	0.036***	0.026
	t(α)	[4.335]	[3.860]	[0.675]	[4.139]	[3.602]	[0.688]
MOM 3-week	α	0.027**	0.022**	-0.007	0.020**	0.014	-0.006
	t(α)	[2.503]	[1.976]	[-0.892]	[2.165]	[1.461]	[-0.855]
MOM 4-week	α	0.017	0.018***	-0.007	0.010	0.010	-0.007
	t(α)	[1.579]	[3.218]	[-0.866]	[1.100]	[1.051]	[-0.827]
PRCVOLM	α	-0.081***	-0.008**	-0.024*	-0.087***	-0.014	-0.023*
	t(α)	[-4.174]	[-2.305]	[-1.858]	[-4.679]	[-1.170]	[-1.852]
STDPRCVOL	α	-0.074***	-0.002	-0.018	-0.081***	-0.009	-0.017
	t(α)	[-3.880]	[-0.121]	[-1.486]	[-4.423]	[-0.737]	[-1.471]

Panel B		M1	M2	M3	M4	M5	M6
AGE	α	-0.014	-0.013	-0.030	-0.017	-0.016	-0.030
	t(α)	[-1.204]	[-1.073]	[-0.640]	[-1.396]	[-1.284]	[-0.642]
MOM 8-week	α	-0.004	-0.001	-0.025	-0.011	-0.010	-0.025
	t(α)	[-0.318]	[-0.073]	[-0.634]	[-1.116]	[-0.915]	[-0.649]
MOM 16-week	α	-0.014	-0.009	-0.028	-0.018	-0.013	-0.027
	t(α)	[-1.092]	[-0.646]	[-0.566]	[-1.473]	[-1.046]	[-0.562]
MOM 50-week	α	-0.030**	-0.007	-0.029	-0.036***	-0.014	-0.028
	t(α)	[-2.325]	[-0.568]	[-0.665]	[-3.001]	[-1.193]	[-0.664]
MOM 100-week	α	0.010	0.011	0.005	0.009	0.010	0.005
	t(α)	[1.081]	[1.148]	[0.478]	[0.957]	[1.010]	[0.480]
VOLM	α	-0.055***	0.010***	-0.005	-0.061***	0.004	-0.004
	t(α)	[-2.942]	[3.032]	[-0.368]	[-3.384]	[0.311]	[-0.320]
VOLMSCALED	α	-0.048***	-0.013***	-0.030***	-0.055***	-0.020**	-0.029***
	t(α)	[-3.777]	[-4.585]	[-2.958]	[-4.670]	[-2.009]	[-3.033]
BETA	α	-0.012	-0.019*	-0.024**	-0.016*	-0.024**	-0.023
	t(α)	[-1.206]	[-1.863]	[-2.294]	[-1.714]	[-2.478]	[-0.583]
BETA SQ	α	-0.010	-0.016	-0.020**	-0.014	-0.020**	-0.020
	t(α)	[-0.980]	[-1.549]	[-1.978]	[-1.455]	[-2.118]	[-0.498]
IDIOVOL	α	0.026**	0.018***	0.034***	0.029**	0.021	0.034***
	t(α)	[2.004]	[5.359]	[2.657]	[2.220]	[1.565]	[2.656]
RETVOL	α	0.041**	0.028***	0.041***	0.043***	0.030*	0.041***
	t(α)	[2.589]	[2.732]	[2.619]	[2.722]	[1.870]	[2.621]
RETSKEW	α	0.011	0.004	-0.004	0.006	-0.003	-0.003
	t(α)	[1.348]	[0.448]	[-0.527]	[0.796]	[-0.398]	[-0.462]
RETKURT	α	0.012	0.006	0.015*	0.013	0.008	0.015*
	t(α)	[1.342]	[0.694]	[1.667]	[1.528]	[0.891]	[1.662]
MAXRET	α	0.052***	0.043***	0.056***	0.052***	0.043***	0.056
	t(α)	[3.500]	[2.803]	[3.710]	[3.486]	[2.783]	[0.944]
DELAY	α	0.005	0.007	0.017	0.007	0.010	0.017
	t(α)	[0.462]	[0.663]	[1.631]	[0.685]	[0.917]	[1.617]
DAMIHUD	α	0.066***	0.018	0.034*	0.073***	0.025	0.033*
	t(α)	[3.338]	[1.014]	[1.893]	[3.780]***	[1.449]	[1.876]

(*continued on next page*)

1-3 include three specifications of the LTW three-factor model (Liu et al., 2022). Models 4-6 examine the incremental effects of the ST factor.

Panel A reports the analysis of the nine anomalies identified by Liu et al. (2022) and our ST strategy, confirming the findings of Liu et al. (2022) that their three-factor model (M3) can explain all nine return anomalies in the crypto market. Conversely, the LTW three-factor model did not explain the ST effect (Table 3). When combined with the market and size factor, an additional ST factor can explain eight of the ten anomalies (M5); however, the ST factor cannot explain short-term momentum (one- and two-week momentum effects). Finally, combining the ST factor with the three existing factors produces an apparent benefit, as this four-factor model (M6) can explain all ten anomalies.

We extend our factor analysis to other anomalies. Panel B includes the insignificant anomalies in Liu et al. (2022). Panel C identifies new anomalies relevant to the prospect theory and skewness. The three-factor model (M3) at a 5% significance cannot explain some new

Table 5 (*Continued*)

Panel C		M1	M2	M3	M4	M5	M6
TK	α	-0.016	-0.011	-0.028**	-0.020*	-0.016	-0.027**
	t(α)	[-1.311]	[-0.906]	[-2.390]	[-1.739]	[-1.357]	[-2.375]
SKEW	α	-0.005	-0.007	-0.006	-0.005	-0.007	-0.006
	t(α)	[-0.746]	[-1.071]	[-0.847]	[-0.757]	[-1.086]	[-0.835]
COSKEW	α	-0.010	-0.009	0.000	-0.005	-0.003	0.000
	t(α)	[-1.068]	[-0.877]	[0.008]	[-0.570]	[-0.322]	[-0.003]
ISKEW	α	-0.004	-0.010	-0.018**	-0.008	-0.014*	-0.017**
	t(α)	[-0.488]	[-1.113]	[-2.141]	[-1.004]	[-1.745]	[-2.154]
DBETA	α	-0.002	-0.005	-0.003	-0.002	-0.005	-0.003
	t(α)	[-0.169]	[-0.513]	[-0.308]	[-0.182]	[-0.530]	[-0.296]

Panel D	M1	M2	M3	M4	M5	M6
One-tail ($\|t\|$ >= 2.336)	13	9	6	13	4	4
Two-tail ($\|t\|$ >= 2.588)	11	8	4	13	3	3

Table 5 presents the details of the regression explaining the crypto excess returns in quintile portfolios using the following asset pricing model specifications.

$$R_i - R_f = \alpha^i + \beta_1^i CMKT + \epsilon_i, \tag{M1}$$

$$R_i - R_f = \alpha^i + \beta_1^i CMKT + \beta_2^i SIZE + \epsilon_i, \tag{M2}$$

$$R_i - R_f = \alpha^i + \beta_1^i CMKT + \beta_2^i SIZE + \beta_3^i MOM + \epsilon_i, \tag{M3}$$

$$R_i - R_f = \alpha^i + \beta_1^i CMKT + \beta_2^i ST + \epsilon_i, \tag{M4}$$

$$R_i - R_f = \alpha^i + \beta_1^i CMKT + \beta_2^i SIZE + \beta_3^i ST + \epsilon_i, \tag{M5}$$

$$R_i - R_f = \alpha^i + \beta_1^i CMKT + \beta_2^i SIZE + \beta_3^i MOM + \beta_4^i ST + \epsilon_i. \tag{M6}$$

The sample consists of actively traded cryptos with a market capitalization of over 1 million USD within the sample period from January 2014 to June 2021, including 391 weeks. The analysis is based on the weekly returns of VW portfolios and factor construction regimes. Panel A reports the significant anomalies in Liu et al. (2022). Panel B shows the insignificant anomalies reported by Liu et al. (2022). Panel C reports the behavioral anomalies, including the prospect theory value, skewness, co-skewness, idiosyncratic skewness, and downside beta. Panel D summarizes the statistical significance of all Panels A to C anomalies. The t-statistics reported in parentheses are based on the Newey and West (1987) standard errors. ***, **, and * denote significant levels at 1%, 5%, and 10%, respectively.

anomalies, including VOLMSCALED, BETA (betting against BETA), IDIOVOL, RETVOL, MAXRET, TK, and ISKEW. Replacing the MOM factor with the ST factor (M5) can explain IDIOVOL, RETVOL, TK, and ISKEW. Interestingly, combining the MOM and ST reduces the explanatory power of these anomalies (M6). The results for M6 resembled those of M3 (size with momentum) more than those of M5 (size with ST).

Panel D summarizes the number of significant anomalies at 1% for the model. The new three-factor model, including market, size, and ST, is a strong contender among the specifications. It can explain as much as the combined model does, suggesting that size and ST are the two key factors in the crypto market. Momentum factors are essential for explaining momentum-related anomalies. The ST factor performed better when the comparison was made outside of the momentum types of anomalies. This new three-factor model, consisting of the market, size, and ST factors in Column (5), can be an alternative risk factor model to the existing LTW three-factor model in the crypto market.

5. Further analyses and robustness test

5.1. The salience of cryptos as an asset class

Salience is determined relative to the average market payoff, compared to alternative investment. Comparing the salience of crypto returns with other assets allows a better understanding of the potential influence of the salience of this new asset class on fund flows into crypto assets.

This section examined the salience effect of cryptos compared with other investment opportunities. To this end, we considered a group of 50 investment instruments, including indices of equity and bonds, major exchange rates, and commodities (Appendix Table A.2). We constructed a salience measure using the 50-return series and the returns of the cryptocurrency index. When the crypto market return is more salient, we anticipate a lower return in the subsequent period.

Panel B of Table 6 summarizes the crypto returns in quintiles of the crypto salience measure, applying Equation (4) for the 51 assets universe. The sample was divided into five groups according to the crypto market's weekly ST measures. We then report the excess return for the following week, calculated by deducting the EW return of the 51 assets from the crypto market index return. The results indicate that following the most downward salience period, excess crypto returns are significantly higher than those following the most upward salience. Calculating the mean spread between the high and low ST periods is -2.19% with a t-value of -2.1 weekly. In other words, compared to other investment opportunities, the salience of the crypto market return negatively predicts future return of the asset class.

Cong et al. (2021) showed that investor sentiment toward an asset can influence the average crypto market payoff, which our evidence extends this by showing that the salience of the crypto index return is a source of investor sentiment that affects its returns.

We also considered the possible cross-sectional ST effect in this 51-asset universe, presenting the ST effect using the 50 instruments and the crypto market index in the Online Appendix Table OA4. The findings further confirm that the ST effect is behavioral and not observable in traditional asset markets, where fundamental information is essential for investors' decisions. In other words, allocating capital among these assets in the global financial market is more efficient and less influenced by salience bias.

Table 6
The salience of cryptos as an asset class among the investment opportunities — weekly returns.

Panel A	1 (Low Period)	2	3	4	5 (High Period)
Mean ST	-0.0127	-0.0017	0.0000	0.0017	0.0098

Panel B	1 (Low Period)	2	3	4	5 (High Period)
Mean	1.77%	1.58%	3.34%	0.39%	-0.42%
Maximum	65.96%	32.11%	33.88%	27.04%	27.13%
Median	12.05%	4.09%	4.60%	-6.20%	0.63%
Minimum	-19.84%	-34.03%	-19.24%	-22.01%	-23.72%

Panel C	1 (Low Period)	2	3	4	5 (High Period)
1 (Low)	0.0257***	0.0150**	0.0342**	0.0087	0.0163
	[3.328]	[2.004]	[2.531]	[0.572]	[1.493]
2	0.0034	-0.0035	0.0056	0.0019	-0.0076
	[0.837]	[-0.719]	[1.036]	[0.245]	[-1.307]
3	0.0047	-0.0021	-0.0067	0.0024	0.0009
	[1.141]	[-0.386]	[-1.319]	[0.460]	[0.182]
4	-0.0033	-0.0125**	-0.0024	-0.0066	-0.0010
	[-0.755]	[-2.364]	[-0.570]	[-1.086]	[-0.215]
5 (High)	-0.0101*	-0.0106	-0.0203**	-0.0129*	-0.0157**
	[-1.695]	[-1.554]	[-2.569]	[-1.740]	[-2.584]
ST High - Low	-0.0358***	-0.0256**	-0.0545***	-0.0216	-0.0319**
	[-3.164]	[-2.540]	[-3.024]	[-1.088]	[-2.359]

Table 6 reports the crypto-related measures in different salience among 51 assets, including equity indexes, credit indexes, foreign exchanges, and futures. The complete list of the investment instruments is presented in Table A.2. The asset return is calculated weekly. The groups' number indicates the quintile portfolio in which crypto salience is among all assets; 1 represents the most down-salience quintile period, and 5 represents the most up-salience quintile period. Panel A lists the mean ST measure in each quintile period. Panel B has the crypto market index's mean, median, maximum, and minimum excess returns (compared to the 50 assets' equal-weighted return) for the following month. Panel C presents the single ST cross-sectional sorting results among the cryptos in each quintile period. The *t*-statistics reported in parentheses are based on the Newey and West (1987) standard error.

Nevertheless, the salience of return in the crypto market can serve as a signal that may further exacerbate the cross-sectional ST effect. We further studied whether the time-series salience effect of the crypto market index affects the cross-sectional salience effects documented in the previous sections. Panel C in Table 6 reports the cross-sectional ST effect in the five quintiles of the subperiods sorted by the crypto index's salience measure for the 51 assets (Panel A). The result shows that when crypto as an asset class is more salient, the cross-sectional salience effects are stronger, regardless of upward or downward salience. The cross-sectional ST effect measured by the high-low rows was highly significant in most down- and up-salience columns, and we observed an "unconditional" cross-sectional salience effect. The strongest cross-sectional salience effect for the non-salience period is in Group 3, suggesting that specialized crypto investors (under-diversified) do not consider the relative movement of cryptos to other investments. This type of investor is a major driver of the salience effect in crypto markets.[6]

5.2. Uncertainty and attention effect

Cakici and Zaremba (2022) showed that the ST effect, as a mispricing phenomenon, is more evident following extreme market states (such as high economic uncertainty and volatility). We examined whether a similar mechanism plays a role in the crypto markets. Following Cakici and Zaremba (2022), we partitioned the entire sample period into high and low uncertainty subperiods using various uncertainty measures. We selected the traditional measures of financial market uncertainty, including the CBOE VIX index and the Federal Reverse Bank economic policy uncertainty index[7] (EUC) developed by Baker et al. (2016).

Table 7 reports the variations of the cross-sectional ST effects in the five periods sorted by the uncertainty indexes, showing the average weekly ST high-low portfolio returns following the formation periods that fall into one of these five subperiods.

Unlike the equity market finding of Cakici and Zaremba (2022), we found that the ST effect is stronger (measured by a high-minus-low on the ST strategy) in the crypto market when uncertainty is low in the equity market, as shown in Panel A (VIX) or the economy in Panel B (UNC). This finding is consistent with the conjecture that salience investors are thrill-seekers; they are more active in the crypto market when the alternative market is relatively quiet (with less volatility). This finding is also consistent with our analyses of the cross-sectional ST effect on the time-series salience of the crypto asset class among the other 50 assets; when the crypto market is more salient, either upside or downside, the cross-sectional salience effects are pronounced in the crypto markets.

Furthermore, we considered the effects of uncertainty on the crypto market. We used the past month's volatility of daily Bitcoin returns as the crypto volatility index (BTC VOL).[8] Panel C shows that if we compare the cross-sectional ST effect in high and low BTC VOL periods, the ST effect is stronger in high BTC VOL periods consistent with Cakici and Zaremba (2022), who examined the global equity market. This finding suggests that underlying market uncertainty is an essential determinant of the ST effect.[9]

[6] Findings in this section are also robustly documented in the monthly analyses reported in Table AO5.

[7] https://fred.stlouisfed.org/series/USEPUINDXD.

[8] The CVI (crypto vol index) was created in 2019, but we have a longer sample period than CVI; therefore, we constructed our own measurements.

[9] We obtain the same conclusion from that of the equal-weighted portfolio returns (Table AO6).

Table 7
The salience effect of crypto market — uncertainty and attentions.

	Panel A: Uncertainty Measured by VIX					
	1 (Low)	2	3	4	5 (High)	High - Low
High VIX	0.0084	0.0035	0.0001	-0.0037	-0.0112	-0.0197
Low VIX	0.0316	-0.0027	0.0005	-0.0063	-0.0169	-0.0485
High - Low	-0.0232**	0.0061	-0.0004	0.0026	0.0057	0.0288**
t-Stat	[-2.368]	[1.212]	[-0.078]	[0.598]	[0.936]	[2.424]

	Panel B: Uncertainty Measured by UNC					
	1 (Low)	2	3	4	5 (High)	High - Low
High UNC	0.0068	-0.0002	0.0049	-0.0008	-0.0155	-0.0223
Low UNC	0.0331	0.0010	-0.0043	-0.0092	-0.0126	-0.0457
High - Low	-0.0263***	-0.0012	0.0093**	0.0084*	-0.0029	0.0234*
t-Stat	[-2.696]	[-0.235]	[2.091]	[1.914]	[-0.483]	[1.798]

	Panel C: Uncertainty Measured by BTC VOL					
	1 (Low)	2	3	4	5 (High)	High - Low
High BTC VOL	0.0207	0.0017	-0.0025	-0.0043	-0.0160	-0.0366
Low BTC VOL	0.0193	-0.0009	0.0031	-0.0058	-0.0121	-0.0314
High - Low	0.0014	0.0026	-0.0056**	0.0015	-0.0038	-0.0053**
t-Stat	[0.550]	[-0.126]	[-2.307]	[-0.434]	[0.141]	[-2.350]

	Panel D: Attention Measured by Google Search Index					
	1 (Low)	2	3	4	5 (High)	High - Low
High Google Search	0.0240	-0.0008	-0.0011	-0.0065	-0.0162	-0.0402
Low Google Search	0.0124	0.0036	0.0037	-0.0022	-0.0090	-0.0214
High - Low	0.0116	-0.0044	-0.0048	-0.0042	-0.0072	-0.0188*
t-Stat	[1.452]	[-0.991]	[-1.222]	[-1.056]	[-1.220]	[-1.678]

	Panel E: Attention Measured by BTC Trading Volume					
	1 (Low)	2	3	4	5 (High)	High - Low
High BTC Volume	0.0229	0.0026	-0.0007	-0.0014	-0.0101	-0.0330
Low BTC Volume	0.0075	0.0074	-0.0028	0.0017	-0.0181	-0.0256
High - Low	0.0154	-0.0048	0.0021	-0.0031	0.0080	-0.0074**
t-Stat	[1.714]	[-0.716]	[0.422]	[-0.668]	[1.249]	[-2.141]

Table 7 reports the average weekly returns of the single-sorted portfolios using the salience theory, with the full sample splitting into high and low uncertainty and attention periods. The sample periods are split into the high and low periods by the median of the uncertainty indexes: VIX (Panel A), UNC (Panel B), the volatility of Bitcoin returns (Panel C), Google search index on cryptocurrency in the formation period (Panel D), and the trading volume of the Bitcoin in the formation period (Panel E). Each week, the assets are sorted into quintiles according to the salience effect measure in the prior week. Each portfolio is held for one week. The portfolio return is constructed in an equal-weighted manner. The "High - Low" row reports the average return difference between the quintile portfolios in high and low uncertainty periods. The "*t*-Stat" row reports the Newey-West robust *t*-statistic.

Attracting salience investors is necessary for the ST effect, and BTC volatility may also be a proxy for investor attention. To understand the effect of attention, we studied two proxies for investor attention in Panels D (Google Search Trends) and E (BTC volume), confirming that the ST effect is stronger when investor attention is relatively higher.

Overall, our analyses suggest that the cross-sectional crypto market's ST effect positively correlates with uncertainty and attention in the crypto market but negatively correlates with uncertainty in the stock market and economy. These findings further confirm that investors influenced by salience bias will likely be risk-seekers. They also highlight the potential diversification effect of cryptos as a non-fundamental investment asset class with a return dynamic different from other traditional asset classes (Chuen et al., 2017; Hu et al., 2019).

5.3. Comparing ST and other factors

5.3.1. Salience, market beta, and idiosyncratic volatility

This section used double sorting to study the interactions between ST and systematic and idiosyncratic risk. Table 8 reports the weekly excess returns of crypto portfolios independently sorted by ST and the two factors.

Panel A of Table 8 reports the double sorting between ST and the crypto market beta. The ST effect was much more substantial in high beta cryptos (Groups 4 and 5). This finding is consistent with the ST in that being systematically important in the crypto market may modify the context of the salience-biased investors' subjective weighting. In other words, the historically high beta, suggesting more extreme co-movement with average peers, will amplify salience bias. In contrast, beta cannot explain the cross-sectional returns within the ST groups. The exception is the lowest ST group, in which a higher beta earns a higher return.

Cakici and Zaremba (2022) show that markets with high average idiosyncratic risk observe higher ST effects that align with the arbitrage explanation limits. Panel B of Table 8 reports the double sorting of ST and IVOL in the crypto market, indicating that the ST effect differs from the IVOL effect on cross-sectional crypto returns. The ST effects were the strongest in the middle IVOL sort (Groups 2, 3, and 4). highlighting the difference between the crypto and equity markets. This result suggests that a high IVOL does not limit the "arbitrageurs" from correcting ST

Table 8
Salience effect, market beta, and idiosyncratic volatility.

	1 (Low)	2	3	4	5 (High)	High - Low	*t*-Stat
	Panel A: Sorted by ST Controlling for Market Beta						
Equal-Weighted							
1 (Low)	-0.009	0.032	0.020	0.035	0.027	0.035**	[2.556]
2	0.007	0.003	0.002	-0.001	0.009	0.002	[1.004]
3	-0.005	0.000	0.001	0.009	0.001	0.007	[1.167]
4	-0.016	-0.009	0.000	0.000	-0.004	0.012	[1.177]
5 (High)	-0.015	-0.006	-0.011	-0.014	-0.017	-0.002	[-0.380]
High - Low	-0.006	-0.038	-0.031**	-0.049***	-0.044***		
	[-0.723]	[-1.443]	[-2.292]	[-3.835]	[-3.334]		
Value-Weighted							
1 (Low)	0.038	0.050	0.039	0.049	0.067	0.029*	[1.703]
2	0.021	0.013	0.015	0.014	0.023	0.002	[1.085]
3	0.015	0.009	0.005	0.020	0.013	-0.001	[0.153]
4	0.001	0.008	0.011	0.012	0.021	0.020	[1.437]
5 (High)	0.065	0.018	0.002	0.000	0.009	-0.056	[-2.195]
High - Low	0.027	-0.032	-0.037	-0.049**	-0.058***		
	[1.272]	[-0.472]	[-1.642]	[-2.208]	[-3.249]		

	1 (Low)	2	3	4	5 (High)	High - Low	*t*-Stat
	Panel B: Sorted by ST Controlling for Idiosyncratic Volatility						
Equal-Weighted							
1 (Low)	0.018	0.024	0.034	0.021	0.006	-0.011**	[-2.428]
2	0.008	0.008	0.000	0.001	-0.017	-0.026***	[-3.237]
3	0.004	0.000	0.008	-0.007	-0.012	-0.016*	[-1.745]
4	0.010	-0.003	0.001	-0.016	-0.017	-0.028***	[-2.598]
5 (High)	0.002	-0.002	-0.015	-0.021	-0.020	-0.021**	[-2.334]
ST High - Low	-0.016*	-0.025***	-0.049***	-0.042***	-0.026*		
	[-1.882]	[-4.197]	[-5.979]	[-4.542]	[1.886]		
Value-Weighted							
1 (Low)	0.018	0.044	0.065	0.051	0.063	0.045**	[2.441]
2	0.016	0.015	0.013	0.017	0.009	-0.007	[-0.742]
3	0.013	0.011	0.016	0.008	0.024	0.011	[0.487]
4	0.020	0.009	0.014	0.014	0.009	-0.011	[-0.364]
5 (High)	0.009	0.008	-0.004	-0.005	0.032	0.023	[0.387]
ST High - Low	-0.009	-0.036***	-0.069***	-0.056***	-0.031		
	[-0.880]	[-3.819]	[-6.395]	[-4.135]	[-1.078]		

Table 8 presents the average weekly returns of the double-sorted portfolios of the ST measure, controlling for other factors. The sample consists of actively traded cryptos with a market capitalization of over 1 million USD within the sample period from January 2014 to June 2021. The cryptos were sorted independently into 5×5 groups depending on the ST measure and existing crypto risk factors each week. Each portfolio was held for one week. We reported the one week-ahead excess returns of each portfolio with EW and VW constructions on the grid. The portfolio sorted by ST is reported in rows, and the portfolio sorted by the existing factors is reported in columns. Using the corresponding sorting variable, the "High - Low" row reports the average return difference between the highest and lowest sorting value portfolios. The "*t*-Stat" row reports the Newey-West robust *t*-statistic. Panel A presents the portfolio returns with the market beta's control variables, and Panel B presents idiosyncratic volatility.

mispricing, or the limit of arbitrage is less of an explanation in this market with no fundamentals. Arbitrageurs are unlikely to exist in these markets, only speculators.

5.3.2. Salience, prospect theory, and preference for skewness

Bordalo et al. (2013a) pointed out that the ST and the prospect theory of Kahneman and Tversky (1979) (KT) assume the decision-makers focus on the probability weights people use to make choices that are different from the objective probability. The primary difference between the salience theory of decision-making and prospect theory is that in ST, these weights depend on the actual payoffs and their salience (a broader context). Bordalo et al. (2013a) showed that, ST and KT will produce similar decision weights in many cases; however, ST will produce different probability weighting when small probabilities are not attached to salient payoffs or when lotteries are correlated. Which of these decision systems provides a more accurate description of a given market is an empirical question. Thoma (2020) followed Barberis et al. (2016) and showed that cryptos with high (low) prospect theory values earn low (high) subsequent returns using monthly historical distribution analyses. They confirm that a high prospect theory value exhibits a significant positive skew, which is more likely to distort the weighting, making it different from the standard expectation model.

Moreover, Bordalo et al. (2013a) theoretically predicted and contributed to understanding the preference for positive skewness. They demonstrated that when certain asset payoffs "stand out" relative to the market, they can distort the perception of asset-specific risks and, consequently, in asset prices due to salience. This finding provides insight into why the right-skewed assets tend to be overvalued.

This section empirically analyzed the relationship among the salience effect, prospect theory, and skewness on cross-sectional crypto returns. The prospect theory value is constructed based on a standard approach specified for stock returns (Barberis et al., 2016). One exception is that we selected a relatively short estimation period to form the prospect theory value. We used daily returns within the past one-month look-back period for the weekly crypto-return analysis. This setup aligns with the shorter investor horizon in the crypto market than

Table 9
Fama-MacBeth cross-sectional regressions — behavioral anomalies.

Panel A	(1)	(2)	(3)	(4)	(5)
ST	-0.306***	-0.381***	-0.311***	-0.365***	-0.307***
	[-3.146]	[-3.940]	[-3.229]	[-3.857]	[-2.928]
TK	0.141**				
	[2.587]				
SKEW		-0.003			
		[-1.523]			
COSKEW			-0.830		
			[-0.196]		
ISKEW				-0.003	
				[-1.240]	
DBETA					-0.002
					[-0.629]
Intercept	0.008	0.000	0.001	0.000	0.001
	[1.478]	[0.063]	[0.251]	[0.103]	[0.187]
Avg. R^2	0.149	0.129	0.1453	0.1314	0.1405

Panel B	ST	TK	SKEW	COSKEW	ISKEW	DBETA
ST	1.000					
TK	-0.310	1.000				
SKEW	-0.028	0.234	1.000			
COSKEW	0.043	0.003	0.030	1.000		
ISKEW	-0.054	-0.001	0.603	-0.087	1.000	
DBETA	-0.013	-0.004	0.013	-0.354	0.071	1.000

Table 9 reports the estimated regression coefficients of the *t*-statistics from Fama-MacBeth cross-sectional regressions for crypto returns (Panel A) and the correlation matrix among behavioral anomaly measures (Panel B). The sample consists of actively traded cryptos with a market capitalization of over 1 million USD within the sample period from January 2014 to June 2021. The regression is based on weekly returns with 391 different periods. The Fama-MacBeth is performed using weekly returns. ST is the salience theory measure. TK is the prospective theory value. SKEW is the daily return skewness. COSKEW is the co-skewness of the daily returns with the market returns. ISKEW is the idiosyncratic skewness of the residuals from the market model. DBETA is the downside beta estimated from the regression of the daily excess crypto return on the daily market return. The variable definition is specified in Table A.1. The *t*-statistics reported in brackets are based on the Newey and West (1987) standard error.

in stock markets. Given the short existence of the crypto market, using a short-term formation period enables us to retain most observations in our sample period. Appendix B presents the detailed construction of prospect theory value.

We compared the pairwise cross-sectional predictability of these behavioral characteristics in the crypto market. Panel A of Table 9 reports the Fama-MacBeth regressions, and Panel B reports the pairwise correlations among the behavioral characteristics. Furthermore, ST dominates all the other measures in explaining cross-sectional crypto returns, particularly for skewness-related measures and downside risks. This result is consistent with the theoretical predictions of Bordalo et al. (2013a). Additionally, KT measures negatively correlate with ST in the crypto market.[10]

Overall, these findings support the link between these measurements. Our study further proves the link between ST and other behavioral theories. The ST differs from prospect theory in the crypto market and describes of cross-sectional crypto pricing well.[11]

5.3.3. *Salience and size effect*

In the equity market, smaller firms behave differently than their larger counterparts in the context of cross-sectional return anomalies (Hong et al., 2000; Fama and French, 2008). This behavior may be due to lower liquidity — resulting in stronger anomalies — and a weaker information environment with fewer news watchers to start some of the trends for momentum traders to chase, resulting in weaker anomalies (Cai et al., 2023). Cakici and Zaremba (2022) show that the salience anomaly appears to be exclusively a microcap phenomenon (accounting for only 3% of the market cap).

We start with the independent double sorting in Panel A of Table 10 to study the interactions between ST and the size effect. A key observation is that these two factors are important and independent. The ST effects were stronger in the medium and large size groups (3, 4, and 5 size groups) and vice versa. This finding highlights a key difference between crypto and equity markets. The ST mispricing effect in the crypto market is not confined to the smallest securities as documented in the international equity market Cakici and Zaremba (2022). Notably, most cryptos are relatively small, with a median market cap of approximately 10 million USD, piratically considered a microcap in the equity market.

We replicated the size test of Cakici and Zaremba (2022) in Panel B of Table 10 to further study the microcap argument. We double-sorted the cryptos independently using ST and market cap and grouped them according to their representation of the total market cap (Cakici and Zaremba, 2022). "Big" cryptos refer to the largest, which account for 90% of the total market capitalization, and "small" cryptos refer to those constituting the next 7% of the market capitalization; "micro" cryptos are the smallest, accounting for the remaining 3% of the market.

Consistent with their findings, we show that ST effects are prominent in the micro-size cryptos with both EW and VW (bottom 3% in capitalization, but account for 87% of the number of cryptos on average). The small cryptos (middle 7% in market cap and 11% in the number of cryptos) also show a significant ST effect on the EW portfolio. The largest cryptos, which comprise 90% of the market share and only have approximately 12 cryptos, show no significant ST effect.

One concern is the accessibility of the returns from the smallest (in terms of the market cap) cryptocurrencies in the trading strategies. We re-examine the salience effect, excluding cryptocurrencies with market caps of less than 10, 25, and 50 million USD. The salience effect remains, especially for equally weighted portfolios. Furthermore, we retested the long-short portfolio using the top 100 cryptocurrencies (ranked by market cap) to eliminate the concern that the salience strategy return may only be obtained in microcap cryptocurrencies. The salience effect is robust for the largest and most liquid cryptocurrencies. The salience effect is the strongest among the 100 largest cryptocurrencies, judging by the magnitude of the high-low return and *t*-values. We present the empirical results in the Online Appendix Table OA9.

Overall, these findings provide two further insights into the effect of ST in the crypto market. First, although the ST effect is more prominent in the crypto market, there is still a predictable difference in the effect of the ST on pricing. The largest cryptos are more likely to attract institutional investors' attention given their size and liquidity, which match the size of the investment. With more relatively sophisticated investors in these cryptos, pricing is less influenced by the ST bias, confirming that ST is a behavioral bias moderated by investor sophistication. This finding suggests that, as the markets have developed, regulated, and integrated with mainstream finance, sophisticated investors reduce the influence of behavioral bias in this market. Second, mispricing is more relevant to micro cryptos, which account for 3% of the market cap; however, these cryptos account for approximately 87% of the number of cryptos. This result is still economically important as the market efficiency of the small but numerous cryptos would be essential in determining whether cryptos can become an asset class to promote innovative finance and distribution effectively. As the market develops, micro cryptos may become leaders in their fields.

5.3.4. *Salience, momentum, and reversal*

Section 4 suggested that ST can replace momentum in explaining other cross-sectional return variations. Cosemans and Frehen (2021)

[10] We obtained a similar conclusion from monthly return analysis. The results are presented in Table AO7.

[11] The conclusions of double sorting using ST and these alternative behavioral measures are consistent with the findings here (Online Appendix Table OA8).

Table 10
The Salience effect of crypto market — controlling for size effect.

Panel A: Double-sorted by ST and Market Capitalization in Quintiles

	1 (Low)	2	3	4	5 (High)	MC High - Low	*t*-Stat
Equal-Weighted							
1 (Low)	0.073	-0.004	0.001	0.006	0.027	-0.045***	[-3.468]
2	0.028	0.002	-0.005	-0.008	0.002	-0.026***	[-3.443]
3	0.031	0.001	-0.002	-0.003	-0.003	-0.033***	[-4.649]
4	0.016	-0.007	-0.006	-0.010	-0.006	-0.022***	[-3.906]
5 (High)	0.023	-0.023	-0.036	-0.012	-0.035	-0.058***	[-5.491]
ST High - Low	-0.049***	-0.019	-0.037**	-0.018***	-0.063***		
	[-4.062]	[-1.335]	[-2.351]	[-2.829]	[-5.399]		
Value-Weighted							
1 (Low)	0.160	0.061	0.057	0.058	0.048	-0.112***	[-6.425]
2	0.061	0.036	0.022	0.013	0.011	-0.050***	[-5.127]
3	0.067	0.034	0.029	0.020	0.012	-0.055***	[-5.530]
4	0.078	0.030	0.026	0.015	0.011	-0.067***	[-2.732]
5 (High)	0.127	0.037	0.021	0.035	-0.001	-0.128***	[-4.491]
ST High - Low	-0.033	-0.024	-0.036*	-0.022**	-0.049***		
	[-0.632]	[-1.119]	[-2.340]	[-2.703]	[-3.274]		

Panel B: Double-sorted by ST and Market Capitalization in Size Groups

	Equal-weighted				Value-weighted			
	Full	Big	Small	Micro	Full	Big	Small	Micro
Avg. *N*	501.6	11.8	54.3	435.5	501.6	11.8	54.3	435.5
1 (Low)	0.020***	0.046***	0.065***	0.019***	0.054***	0.038***	0.060***	0.059***
	[4.065]	[5.477]	[6.010]	[4.357]	[5.850]	[4.886]	[5.316]	[6.445]
2	0.000	0.017***	0.020***	-0.002	0.013***	0.013**	0.019***	0.011**
	[0.162]	[3.174]	[4.226]	[-0.787]	[2.777]	[2.286]	[3.489]	[2.385]
3	0.000	0.025***	0.011***	-0.001	0.014***	0.024***	0.016***	0.009**
	[0.130]	[4.261]	[2.658]	[-0.266]	[3.275]	[3.815]	[3.112]	[2.365]
4	-0.005**	0.032***	0.017***	-0.006***	0.016***	0.028***	0.016**	0.013***
	[-2.287]	[3.142]	[3.340]	[-2.608]	[3.312]	[2.880]	[2.373]	[2.976]
5 (High)	-0.014***	0.059**	0.002	-0.014***	0.024**	0.057**	0.026	0.016**
	[-4.653]	[2.139]	[0.129]	[-4.739]	[2.518]	[2.094]	[1.433]	[2.325]
ST High - Low	-0.034***	0.013	-0.064***	-0.033***	-0.030**	0.020	-0.034	-0.044***
t-Stat	[-5.223]	[0.450]	[-3.522]	[-6.292]	[-2.226]	[0.689]	[-1.605]	[-3.796]

Table 10 presents the weekly portfolio returns of cryptocurrencies controlling for the size effect. Panel A contains the double-sorted portfolio returns on ST and market capitalization. The cryptos are independently sorted into 5×5 groups based on the weekly ST measure and market capitalization. Each portfolio was held for one week. Panel B shows the average weekly returns of the single-sorted portfolios of cryptocurrencies in different size groups using the salience theory measure. The "Full" columns show the portfolio returns using the full sample. "Big" includes the cryptocurrencies that cover 90% of the total market capitalization of the week, "Small" group covers the next 7% of the total market capitalization, and "Micro" captures the remaining 3%. Each portfolio was held for one week. The sample consists of actively traded cryptos with a market capitalization of over 1 million USD within the sample period from January 2014 to June 2021. According to the ST measure, the cryptos are sorted into quintiles during the portfolio formation period. The row "Avg. N" tracks each size group's average number of cryptocurrencies. Using the corresponding sorting variable, the "High - Low" row reports the average return difference between the highest and lowest sorting value portfolios. The "*t*-Stat" row reports the Newey-West robust *t*-statistic.

and Cakici and Zaremba (2022) showed that ST is closely related to the reversal effect in the equity market literature. In the crypto market, the momentum factor introduced by Liu et al. (2022) is a "reversal" factor in the equity market setting; the strategy does not skip one period (week or month) to allow for potential reversal. This strategy's positive crypto-momentum factor return suggests no simple reversal effect in the crypto market.

When studying the correlation of the factors, we observed that the ST factor premium indeed has a high correlation with the momentum factor premium (27.8% for EV and 46.8% for VW factors).[12]

We further studied the interactions between these two factors using double sorting. Panel A of Table 11 shows that the ST effect is generally stronger than the momentum or reversal effects. The ST effect was observed in four of five quintiles in EW and two of five quintiles in VW when controlling for momentum. In contrast, the momentum or reversal effect was weaker when controlling for the ST effect. This finding explains why including the ST factor can explain the excess return of the momentum strategy, whereas including the momentum factor cannot explain excess return of the ST strategy in Table 5.

We next studied whether our ST results hold when the most recent days (1–3 days) are excluded from the estimation period in a monthly setting. This approach allowed us to elevate the concern that ST is only a reflection of the short-term momentum or reversal effect, following Cakici and Zaremba (2022). The findings are presented in Online Appendix Table OA11. While the magnitude and significance weaken as more days are skipped between the formation and return calculation, the magnitude and significance are still substantial and economically significant. This finding confirms that ST differs from the short-term reversal or momentum effects and highlights the benefit of testing the ST theory in this asset class, which has a different clientele and dynamic from the equity market. This result allowed us to identify the theory's explanatory power more clearly.

Benedetti and Kostovetsky (2021) documented that the ICO underpricing is over 170%, and the price quickly reverses after the first

[12] We present the risk factor correlation table in Table AO10.

Table 11
The salience effect of crypto market — controlling for momentum.

	1 (Low)	2	3	4	5 (High)	MON High - Low	*t*-Stat
	Sorted by ST Controlling for Momentum						
Equal-Weighted							
1 (Low)	0.034	0.034	0.036	0.023	0.004	-0.030**	[-1.996]
2	-0.006	0.003	0.008	0.006	-0.001	0.005	[0.575]
3	0.002	0.000	0.007	0.004	-0.021	-0.023**	[-2.410]
4	0.003	-0.001	0.004	-0.007	-0.038	-0.041***	[-4.659]
5 (High)	-0.024	-0.014	-0.013	-0.029	0.017	0.041**	[2.549]
ST High - Low	-0.058***	-0.048***	-0.048***	-0.052***	0.013		
	[-5.570]	[-3.877]	[-4.469]	[-5.641]	[1.495]		
Value-Weighted							
1 (Low)	0.032	0.043	0.047	0.041	0.075	0.043***	[3.157]
2	-0.011	0.008	0.015	0.022	0.023	0.033***	[3.467]
3	0.002	0.003	0.014	0.011	0.006	0.004	[0.924]
4	0.010	0.004	0.015	0.015	-0.010	-0.019*	[-1.816]
5 (High)	-0.021	0.008	0.014	-0.006	0.047	0.068***	[2.889]
ST High - Low	-0.052***	-0.035	-0.034	-0.047***	-0.028		
	[-3.580]	[-1.605]	[-1.123]	[-3.374]	[-0.874]		

Table 11 presents the average weekly returns of the double-sorted portfolios of the ST measure controlling for the momentum factor. The sample consists of actively traded cryptos with a market capitalization of over 1 million USD within the sample period from January 2014 to June 2021. The cryptos are sorted independently into 5×5 groups based on the weekly ST measure and momentum factor. Each portfolio was held for one week. We reported the one-week-ahead excess returns of each portfolio with EW and VW constructions on the grid. The portfolio sorted by ST is reported in rows, and the portfolio sorted by the existing factors is reported in columns. Using the corresponding sorting variable, the "High - Low" row reports the average return difference between the highest and lowest sorting value portfolios. The "*t*-Stat" row reports the Newey-West robust *t*-statistic.

trading day. To mitigate the concern that ICO underpricing and reversals may be key drivers of our findings, we repeated our study by excluding each crypto's first month of observation. The magnitude and statistical significance only reduced slightly compared to the baseline results.[13] These results further support that ST operates as a distinct price driver, separate from mean-reversal or ICO underpricing mechanisms.

5.4. Other robustness tests

We also performed other robustness tests, showing that the ST effect is time varying in the yearly sub-sample analysis. The ST effect is generally observed, with negative EW strategy returns for all eight years; the ST effect was statistically significant in five of the eight years. We studied the robustness of the ST effect for different formation periods and altered the salience effect specification. These findings and discussions can be found in the Online Appendix.

6. Conclusion

The introduction of Bitcoin has provided an enormous opportunity to experiment with decentralized technology for trading and recording financial transactions. Simultaneously, the increasing appetite for speculation has fueled the rapid growth of the crypto market. Since 2009, cryptos have become a new asset class within a decade of their first existence. The critical role of social media in developing this asset class cannot be overstated, and it continues to influence pricing. This study contributes to the literature on crypto pricing by formally examining how investors' disproportional attention to salience outcomes influences time-series and cross-sectional crypto pricing predictably.

Salience theory is intuitive yet embedded in the fundamental theory of context-dependent preference. Salience thinkers cannot objectively evaluate the distribution of outcomes, especially when other objective measures are lacking, and salience is amplified through social media. The salience effect documented in this study is the strongest in the ST literature, which is unsurprising, given that this asset lacks fundamentals and has a concentrated retail clientele. This situation confirms that ST is much more relevant for emerging assets with high uncertainties; however, it is possible that once this asset market becomes more mature and mainstream (with more institutional investors involved), other pricing mechanisms may dominate. Before then, ST offers a close description of the return dynamics in the crypto market.

CRediT authorship contribution statement

Charlie Cai: Conceptualization, Writing- Original draft preparation, Writing- Reviewing and Editing. **Ran Zhao**: Methodology, Software.

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Declaration of competing interest

The authors have no relevant financial or non-financial interests to disclose.

Data availability

Data will be made available on request.

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[13] Empirical results are presented in Online Appendix Table OA12.

Appendix A

A.1. Supplementary tables

Table A.1
Variable definitions.

Variable	Definition
ST	The salience theory measure is calculated from Equation (4) in Section 2.2. We compute the weekly (monthly) ST using a sample period of one week (one month) before the portfolio holding period.
CMKT	The cryptocurrency market return. The market return is based on equal-weighted calculation if not otherwise specified.
BETA	The estimated coefficient β^i_M in the regression $R_i - R_f = \alpha^i + \beta^i_M MKT + \epsilon_t$. The model is estimated using daily returns of the trailing 30 (365) days for the formation week (month).
SIZE	Log last day market capitalization in the portfolio formation week (month).
MOM kW	k-week momentum, as the cumulative return for the past k weeks. MOM represents the lagged one-week return if not otherwise specified.
AGE	Time in friction of year(s) from the listing on Coinmarketcap.com.
IVOL	The idiosyncratic volatility is calculated as the standard deviation of the residuals from the market model $R_i - R_f = \alpha^i + \beta^i_M MKT + \epsilon_t$. The model is estimated using daily returns of the previous 30 (365) days before the week (month).
ILLIQ	The average absolute daily return divided by USD volume in the portfolio formation week (month).
MAX	The maximum daily return of the crypto within the sample period.
MIN	The minimum daily return of the crypto within the sample period.
MCAP	Log last day market capitalization in the portfolio formation week (month).
PRC	Log last day price in the portfolio formation week (month).
MAXDPRC	The maximum price of the portfolio formation week (month).
PRCVOLM	Log average daily volume times price in the portfolio formation week (month).
STDPRCVOL	Log standard deviation of USD volume in the portfolio formation week (month).
VIX	The CBOE published S&P 500 implied volatility index.
UNC	The economic policy uncertainty index developed by Baker et al. (2016).
BTC VOL	The standard deviation of the daily Bitcoin returns within the week (month).
TK	The prospective theory value is computed as specified in Bordalo et al. (2016). The measure is calculated using daily returns from trailing 30 (365) days prior to the formation week (month).
SKEW	The daily return skewness estimated from the trailing one-month crypto returns.
COSKEW	The co-skewness of the daily crypto returns over the one-month window using the approach of Harvey and Siddique (2000).
ISKEW	The idiosyncratic skewness of the residuals from the market model using trailing 30 (365) days before formation week (month).
DBETA	The downside beta estimated from the regression of the daily excess crypto return on the daily market return Ang et al. (2006) over the previous 30 (365) days before formation week (month).

Table A.2
Full list of 51 assets.

Category	Ticker	Description
Crypto (1)	CMKT	Equal-weighted crypto market index
Equity (16)	DIA	Dow Jones Industrial Average
	EFA	iShares MSCI EAFE
	QQQ	NASDAQ 100 Index
	VWO	Vanguard Emerging Markets Stock Index
	RUI	Russell 1000 Index
	RUT	Russell 2000 Index
	RUA	Russell 3000 Index
	EEM	iShares MSCI Emerging Markets
	DAX	German Stock Index DAX 30
	NSE	India Nifty 50 Index
	CAC	France stock market index CAC 40
	NKY	NIKKEI 225 Index
	HSI	Hang Seng Index
	EU50	EURO STOXX 50
	EU100	FTSE Euro 100 Index
	FXI	iShares China Large-Cap
Volatility (4)	VIX	VIX index future (most active)
	VXX	Barclays iPath Series VIX Short-Term Futures ETN
	VSTOXX	EURO STOXX 50 Volatility
	UVXX	ProShares Ultra VIX Short-Term Futures ETF
Forex (8)	USD	Dollar Index Future
	USD/JPY	Japanese Yen Future
	GBP/USD	British Pound Future
	EUR/USD	Euro US Dollar
	AUD/USD	Aust. Dollar
	USD/CAD	Canadian Futures
	USD/TRY	Turkish Lira
	FXE	Invesco CurrencyShares Euro Trust ETF

(*continued on next page*)

Table A.2 (*continued*)

Category	Ticker	Description
Commodity (10)	GDX	VanEck Gold Miners
	GOLD	Gold future (most active)
	XAU/USD	Gold Spot US Dollar
	BRENT	ICE Brent Crude (most active)
	OIL	WTI Crude (most active)
	GAS	Natural Gas (most active)
	SILVER	Silver future (most active)
	COPPER	Copper future (most active)
	CORN	Corn commodity (most active)
	WHEAT	Wheat commodity (most active)
Rate/Credit (9)	HYG	iShares iBoxx High Yield Corporate Bond
	LQD	iShares iBoxx Investment Grade Corporate Bond
	US 2 YR FUT	U.S. 2-year treasury note future (cheapest to deliver)
	US 5 YR FUT	U.S. 5-year treasury note future (cheapest to deliver)
	US 10 YR FUT	U.S. 10-year treasury note future (cheapest to deliver)
	US 30 YR FUT	U.S. 5-year treasury bond future (cheapest to deliver)
	ES 10 YR	Spain 10-year bond yield
	BUND 10 YR	Germany 10-year bond yield
	TRY 2 YR	Turkey 2-year bond yield
Others (3)	IVR	iShares US Real Estate Index
	ARKK	ARK Innovation ETF
	INRG	iShares Global Clean Energy UCITS

Appendix B. Construction of prospect theory value on cryptocurrencies

We follow the standard prospect theory value (PTV) construction process specified in Barberis et al. (2016) for cryptocurrencies. The formation of the prospect theory for stocks looks back to the past 60-month return monthly. Crypto assets emerge in a relatively short period. To avoid losing a majority of the observations for the cryptos, we use daily returns of the crypto assets and form the prospect theory estimation period of 1 month for weekly crypto return analysis and an estimation period of 1 year for the monthly crypto return analysis. We perform robustness checks on the selection of the formation period and find that lengthening the PTV formation period does not alter the main conclusion in our paper. The empirical results remain when we vary the formation period of PTV from 1-week to 1-year for weekly returns and the formation period of PTV from 1-month to 1-year for monthly returns.

Besides the reason for the short time of existence of the crypto market, using daily returns and a shorter PTV estimation period makes the information formation time frame more consistent with the construction of the salience effect measurement used in this paper. We describe the construction of PTV using the 1-month formation period in more detail.

Based on the daily crypto returns, we first define the functional form of the value function as in Kahneman and Tversky (1979).

$$v(x) = \begin{cases} x^{\alpha} & \text{for } x \geq 0 \\ -\lambda(-x)^{\alpha} & \text{for } x < 0 \end{cases}$$

where the parameter α measures the risk aversion, and the λ parameter measures loss aversion. We follow Kahneman and Tversky (1979) and Barberis et al. (2016) and select the functional form of the probability weighting function as

$$w^{+}(P) = \frac{P^{\gamma}}{(P^{\gamma} + (1-P)^{\gamma})^{1/\gamma}}, \qquad w^{-}(P) = \frac{P^{\delta}}{(P^{\delta} + (1-P)^{\delta})^{1/\delta}}$$

where γ and δ are distortion parameters. The values of γ and δ are negatively related to the degree of distortion on probability P.

For the parameter choice, we use the value of the parameters as

$$\alpha = 0.88, \quad \lambda = 2.25, \quad \gamma = 0.61, \quad \delta = 0.69.$$

In unreported empirical results, we shock the parameter selection in certain ranges (varying each parameter from 0.5 to 2 times its original value). The empirical conclusions are consistently the same. We first rank the past 30 days' crypto return in ascending order for the return distribution estimation. Denote m as the number of days with a negative return, and $n = 30 - m$ as the number of days with a positive return. We assume the past 30 days of the crypto returns to have a uniform distribution, i.e., the occurrence probability of each day's return is equal. The return distribution is specified as

$$\left(r_{-m}, \frac{1}{30}; r_{-m+1}, \frac{1}{30}; \dots; r_{-1}, \frac{1}{30}; r_{1}, \frac{1}{30}, \dots, r_{n-1}, \frac{1}{30}; r_{n}, \frac{1}{30}\right).$$

where r_i is the ranked daily crypto returns. Furthermore $i \in \{-m, -m+1, \dots, -1, 1, \dots, n-1, n\}$. r_{-m} represents the lowest crypto returns (most negative) in the past month, and r_n represents the highest (most positive) returns.

If we combine these components, we can define the PVT for the cryptocurrency returns as

$$PTV = \sum_{i=-m}^{-1} v(r_i)\left[w^{-}\left(\frac{m+i+1}{30}\right) - w^{-}\left(\frac{m+i}{30}\right)\right] + \sum_{i=1}^{n} v(r_i)\left[w^{+}\left(\frac{n-i+1}{30}\right) - w^{+}\left(\frac{n-i}{30}\right)\right]. \tag{5}$$

Our paper's construction of the PVT is similar to the empirical specification for stocks (Barberis et al., 2016) and cryptocurrencies (Thoma, 2020).

Appendix C. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jbankfin.2023.107052.

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